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Deep Learning-Based Plant Disease Detection Using Leaf Image Analysis

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Abstract:

Plant disease identification is an important technique for food security in global food safety and enhancing agricultural yield. Automatic inspection by experienced person is an important tool for the plant disease diagnosis, but this traditional method is costly, labor-intensive, time-consuming and can lead to many errors due to visual subjectivity, especially in the context of large scale farms. Recent studies with advanced techniques in the fields of computer vision and deep learning has been conducted in automatic detection of plant diseases from images of plant leaves. In this research, a deep learning approach with integrated with convolutional neural network (CNN), Transfer Learning and FPN which helps in capturing the multi-scale features for better performance on both feature extraction and classification tasks. Image preprocessing and augmentation methods were applied on PlantVillage dataset, and the integrated model was then trained and validated. The experiment shows that the proposed model achieved the highest validation accuracy as 97.22% and the validation loss as 0.0951. In the classification report, the average precision, recall and F1-score of about 97% were also achieved. In addition, the confusion matrix proved that most of the chosen plant disease classes were correctly identified. This research demonstrates the accuracy and effectiveness of the proposed method for the automated detection of plant diseases and shows potential for smart agriculture.

Keywords: Plant Disease Detection, Deep Learning, Xception, Transfer Learning, PlantVillage Dataset

1. Introduction

AI, Computer vision, data mining technology is being applied widely and developing at a rapid pace to make a number of intelligent systems that analyse agricultural data and to support decision making, agriculture has experienced much progress in recent years. However, the outbreak of plant diseases is one of the serious factors that may impact quality, yield and the productivity of crops around the world. Under conditions where adverse environment can result in fast spreads of diseases causing severe economic losses and threaten food security, early and accurate detection of plant diseases becomes very crucial for minimizing damage of crops, increasing the productivity of agricultural sectors and facilitating the practice of agriculture sustainably. Diagnosis based on observation of disease symptoms by agricultural experts is a widely accepted method. It produces the correct diagnosis, however it requires expert experience; it is expensive, slow and time consuming, which are impractical for large-scale crop fields. Besides, it can be biased by the environment and observer. Fortunately, nowadays, with a large volume of labeled images and developments in the deep learning models (CNN, Transfer learning, ResNet, EfficientNet, Vision Transformer) on benchmark data-set (PlantVillage), automated plant disease detection using the images of the leaf is promising.



Figure 1. Representative examples of healthy and diseased plant leaves from the PlantVillage dataset used in this study.

1.1 Problem Statement

Even with such achievements, however, there are several issues associated with current plant disease detection methods. For example, many of the existing detection models necessitate massive computational cost, whereas some models achieve only poor generalization ability on datasets with different scales or in varied environmental conditions. Some other deep learning based models still possess inferior classification ability, in that it fails to correctly distinguish between two plant diseases with a similar appearance. Thus, such defects may limit their application in practice agricultural scenarios in which classification accuracy, cost and computational overhead are equally significant. In summary, the existing models present many constraints in terms of low detection accuracy and computational efficiency for real applications, resulting in the urgent demand for a more advanced and computationally less expensive but highly performant early plant disease diagnosis model.

1.2 Research Objectives

This research focuses on the design and implementation of a deep learning-based automatic plant disease detection model from plant leaf images. This research work focuses on the construction of the plant disease detection framework on the basis of the Xception architecture with the transfer learning method for better classification. It also validates the developed model by employing the benchmark PlantVillage dataset and compares it with other recent deep learning based model approaches available in literature to ensure efficiency. In addition to that, this work aspires to provide an intelligent and accurate system that enables the farmers to detect the plant disease in the early stage to mitigate crop losses and contribute to the development of sustainable agriculture.

1.3 Research Contributions

In this paper, we develop a framework of deep learning to detect diseases automatically in plants using transfer learning in the Xception network architecture. Our proposed system uses well-established computer vision tools to identify diseases and categorize plants effectively. It allows accurate plant leaf picture review and helps make it available as an adaptive framework that can power future smart agriculture initiatives. In experimental tests conducted on the PlantVillage dataset, our proposed model yielded a 97.22% validation accuracy with about 97% recall, precision, and F1 score, establishing its reliability as an automated disease detection tool for plants.

2 Previous Studies:

The early methods of plant disease identification was mainly based on classical machine learning such as SVM, decision tree, random forest, and KNN. Although these methods can obtain good accuracy, they depend on manual selection of features, color, texture, and shape. These methods cannot efficiently and effectively analyze large-scale, complex image datasets. With the development of AI technology, people focus on deep learning technology such as CNN to automatically extract the discriminative features from plant leaf images. Lately, transfer learning, attention mechanism, ViTs, and combined deep learning models are applied to enhance accuracy and robustness. Some representative researches are presented below:

Sharma et al. (2023) [1] presented an attention-based Convolutional Neural Network (CNN) model that aims to improve plant disease classification and localization by paying attention to diseased regions of plant leaves. The attention mechanisms guide the CNN to focus on extracting informative features from infected areas while discarding irrelevant information from background objects. The proposed model, trained on the PlantVillage and real-field image datasets, achieved a classification accuracy of 98.7% and proved to increase localization and classification performance over traditional CNN methods, and increase model robustness under varying image conditions. However, attention modules also increase model complexity and computational costs.

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Wang et al. (2025) [2] developed an improved deep learning model using CNN and Transformer architectures for plant disease identification. The motivation behind the design of the model was to combine the ability of CNNs in capturing local features and the global reasoning capabilities of the vision transformers. The model was trained on a diverse plant disease database (e.g.PlantVillage) and resulted in classification accuracies above 97%. However, the hybrid model needed significant computing power and had scaling issues in real world agricultural scenario.

Sahu et al. (2025) [3] A Hybrid Dilated Convolutional Neural Network architecture was introduced by to perform an accurate prediction of plant disease, where an optimal multiscale features extraction method was proposed along with an attempt to retain useful spatial information. This model was evaluated using a combination of PlantVillage and additional plant disease augmented datasets and showed an accuracy of about 98% overall for disease classification. However, the computational efficiency and training duration was increased as the architecture contained numerous dilated convolution layers for a better performance in identifying diseases.

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Ibrahim et al. (2025) [4] proposed an improved deep learning model for plant disease detection by combining several optimization strategies to boost the classification and generalization ability. They used both PlantVillage and real-field image data sets to train their model and obtained an accuracy of 97.5% for classifying plant disease. Even though their method was capable of generalizing well across several species of plants and diseases, they stated that they should further validate the model by including much more real field data before deployment.

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Patel and Shah (2024) [5] proposed a framework to perform plant disease classification using a Vision Transformer (ViT). The authors utilize the self-attention mechanism of ViTs to learn the global features of the image, thus overcoming the limitations of traditional CNNs in learning global features. The long-range dependency between image patches can be successfully captured, which helps to learn more representative features.The model trained on benchmark datasets, such as PlantVillage, achieved 99.1% classification accuracy, superior to many CNN-based approaches in both accuracy and features extraction. However, the ViT architecture requires a lot of computing power, large memory and vast training data, which makes it less practical in the low-resource agricultural regions.

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Zhao et al. (2025) [6] developed an object detection model based on Mask R-CNN and Faster R-CNN that could be utilized for the automated detection and localization of plant diseases. This framework differentiates itself from other image classification approaches because it identifies not only disease categories, but also the precise position of affected areas on plant leaves, based on their bounding boxes.This model was trained with a collection of plant disease datasets that had bounding-box labels for each affected region and achieved detection accuracies from 63% to 90% (depending on the data quality and labeling precision). Experimental analysis indicated that the two detection models were effective at pinpointing disease symptoms with accuracy, while also achieving dependable results in terms of classification. Yet, this research highlighted the fact that the performance of this model is strongly reliant on the completeness and precision of manual labels, which in turn makes dataset creation time-consuming and costly.

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Ahmed et al. (2025) [7] suggested a multi-scale Convolutional Neural Network (CNN) paired with a Feature Pyramid Network (FPN) in order to achieve better results for plant disease detection through different spatial resolutions of disease symptoms. The proposed framework leverages the

combined features from various convolutional layers in order to assist the model in identifying smaller lesions as well as larger affected regions more accurately. This model was trained using numerous plant disease datasets which are publicly accessible, such as PlantVillage and real-field image datasets. The classification accuracy achieved was an overall score of 99.2%. When experimental tests were performed, it was determined that FPN had a positive effect on the feature representation, therefore enhancing classification outcomes over more traditional CNN models. Furthermore, the presented framework exhibited increased resilience in identifying early symptoms of disease. However, utilizing multi-scale feature extraction led to an increased memory usage and more intensive computational requirements during the training process.

Table 1 summarizes the selected previous studies by comparing their methodologies, datasets, reported accuracies, and major limitations.

Study	Year	Methodology	Dataset	Accuracy	Limitations
Sharma et al.	2023	CNN + Attention	PlantVillage + Field Images	98.7%	High computational complexity
Wang et al.	2025	CNN + Transformer	Multi datasets	>97%	Scalability issues
Sahu et al.	2025	Hybrid Dilated CNN	Plant leaf datasets	~98%	High complexity
Ibrahim et al.	2025	Optimized Deep Learning Model	Combined datasets	97.5%	Needs real-world validation
Patel & Shah.	2024	Vision Transformer (ViT)	Benchmark datasets	99.1%	High computational cost
Zhao et al.	2025	Mask R-CNN, Faster R-CNN	Annotated datasets	63%–90%	Depends on data quality
Ahmed et al.	2025	Multi-scale CNN (FPN)	Multi datasets	99.2%	High memory usage

2. Methodology:

The workflow of the proposed methodology The proposed work utilizes deep learning for automated detection of diseases on plant leaf through an image analysis. The proposed method is based on Image Pre-processing, CNNs, Transfer Learning (TL) and Feature Pyramid Networks (FPN) techniques to optimize and boost the performance in disease classification. In order to address the problems detected in Chapter 2 regarding the generalizations, computational cost, and the accuracy, we proposed a new approach.

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The schematic diagram of the whole system shown in Figure 2.

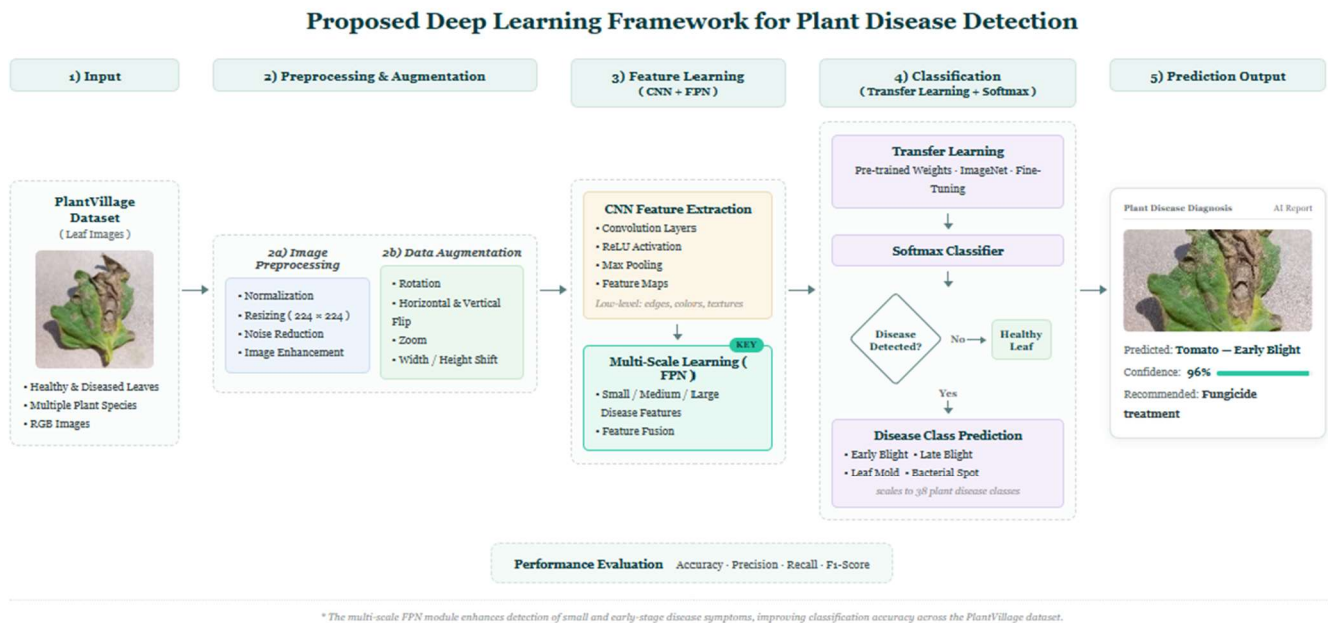


Fig. 1. Overall architecture of the proposed CNN–FPN deep learning framework integrating preprocessing, multi-scale feature learning, transfer learning, and softmax classification for plant disease detection.

Figure 2: Proposed Framework of Plant Disease Detection System

3.1 Input (Dataset)

PlantVillage dataset PlantVillage dataset is one of the widely known dataset for studying on plant disease recognition. It consists of thousands of colored leafimages belonging to healthy, diseasedplants for many crop. The classes that we have selected here from the dataset are as below. Pepper Bell Bacterial Spot, Pepper Bell Healthy, Potato Early Blight The below figures illustrates some sample samplesfrom selected dataset classes.

3.1.1 Classification Dataset

The PlantVillage dataset has become one of the most famous publicly available benchmark dataset to classifying plant diseases. This dataset comprises a total of 54,306 high-quality RGB pictures, captured from multiple crop species under well-controlled settings and contains more than a hundred varieties of plant diseases, healthy or sick. With their highly quality of image and balanced number of entries for different diseases, the dataset was used widely to research a deep learning based approach for recognizing diseases on the plants. For this experiment, three categories of PlantVillage Dataset was extracted to be used which are: Pepper Bell Bacterial Spot, Pepper Bell Healthy, Potato Early Blight, due to contain some examples of both diseases as healthy one that allow to build a system that differentiate diseased samples from the healthy one, and due to the presence of the mentioned plant types and variety of disease that could greatly affects to the yield of plants.

Figure X shows sample pictures of plant with some plant diseases which selected in the PlantVillage dataset such as: Pepper Bell Bacterial Spot, Pepper Bell Healthy and Potato Early Blight.

Pepper Bell Bacterial Spot



Pepper Bell Healthy



Potato Early Blight



Figure 3 Image from Dataset

3.2 Image Preprocessing

Before the proposed deep learning model is trained, all input images will undergo an image preprocessing procedure to obtain consistency, boost the quality of images, and enrich the learnability of the deep learning model. In the case of the PlantVillage dataset, the images show a variety of appearances, so preprocessing is mandatory in order to harmonize input images before feature extraction. Preprocessing procedures remove unnecessary differences between images, thereby helping the deep learning model concentrate on identifying specific features pertaining to the disease in images instead of unrelated information.

Histogram normalization

Original Image



After Preprocessing



(Figure 4: Image Before and After Preprocessing)

3.2.1 Image Resizing

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Each original image is resize to 224 224 pixels, which is the size input that the deep learning model requires as it can be see in the model architecture above. Normalizing the size of each image ensure that each of the input to the model have the same shape. resizing of image has advantages that it makes the computation load smaller, reduces the model training time, can perform batch training without distorting the basic features of the disease on the leaf.

3.2.2 Image Normalization

After images are resized, pixels values are normalized in the range of 0-1 by multiplying the original pixel values of 0-255 by 1/255. The image normalization helps to stabilize numerical values for the optimization algorithm and also enables the algorithm to converge faster and prevent the large pixel values from taking control in the learning process, so that the gradient updates can be more stable and thus the classification accuracy can be boosted up.

3.2.3 Noise Reduction

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Even though images in the PlantVillage dataset are considered quite clean, some small image noise and undesired image appearance variations can still be present. To address this, image denoising methods are applied to remove image artifacts which are irrelevant and harmful to diagnose the disease and not of great interest while retaining the relevant visual disease characteristics (leaf spots, discoloration and texture) so that the convolutional neural network is able to extract useful features.

3.2.4 Image Enhancement

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Image enhancement in this work focuses on providing visually better quality images for the input to the deep learning model for easier extraction of the features. Image enhancement mainly in this work involves resizing of the images to 224 x 224 pixels and normalizing their intensities in the range of [0,1] (which originally were [0,255]). These are the input images for the CNN model.

Normalization makes the model invariant to illumination effects and helps the model converge faster. This results in stable training and convergence of the model, thereby providing better accuracy as the model can learn features based on color changes, lesion shapes, etc rather than just the intensity of the image.

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3.2.5 Data Augmentation

Several data augmentation methods are used during the training of the proposed model to ensure good generalization and avoid over-fitting. Data augmentation helps create additional samples artificially by transforming the existing image in a random way while maintaining the

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same label of that image. Augmentation expands the diversity of the training data, helping the model behave well in various image conditions.

3.2.6 Rotation

Each of the training images is randomly rotated using varying angles. Leaves may naturally present themselves at different orientations so rotating them means the model learns that it should look for signs of disease in any position the leaf happens to be in.

3.2.7 Horizontal and Vertical Flip

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Mirrored versions of the original images are created by using horizontal and vertical flip. They maintain the disease class and augment the diversity of the training data. It makes the model less dependent on the direction of the leaf and enables to perform better generalization.

3.2.8 Zoom

The model randomly zooming to be able to detect disease features at various scales. Some diseases can first be small lesion size, others extend to larger parts of the leaves. By zooming it, we force the model to be able to learn disease signatures irrespective of scale.

3.2.9 Width and Height Shift

The image is horizontally translated to the right or to the left, and it's also translated upwards and downwards to random values. The aim is to avoid the trained model to "fixate" in a specific position of the symptoms of the disease within the image, thus making the model focus on the visual characteristics instead of their precise location. In this way, when the model analyzes images of plant leaves from real environments it is more reliable.

3.3 Feature Learning

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After applying the preprocessing and data augmentation operations, the ready images are supplied into the feature learning module to extract automatically effective visual characteristics from the images of plant leaf, to discriminate between disease leaves and normal ones. Our framework instead of manually designed feature extraction module employ the application of deep learning technologies to learn discriminative feature automatically from training image data. In this proposed feature learning framework, the blend of Convolutional Neural Networks (CNN) , Transfer Learning (TL) ,and Feature Pyramid Networks (FPN) will further contribute to higher classification performance and stronger model stability.

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3.3.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are one of the most popular deep learning approaches applied for image classification problems. The network was especially designed for the analysis

of visual information, automatically extracting high-level features from the images to be processed. Unlike many classical approaches that require manual selection of image features, the CNN learns these characteristics (both low-level and high-level) on its own while being trained on the training data. The model receives a preprocessed image of the plant leaf as the first input. The image goes through several convolutional layers and various learnable filters are used to extract salient image features like leaf shape, texture, color, presence of lesion, etc. After extraction, these features are filtered by an activation function and downsampled by pooling layers. These extracted features are then flattened and used as inputs to fully connected layers where the network learns the connection between extracted image features and the type of plant disease that the leaf has, outputting a classification decision.

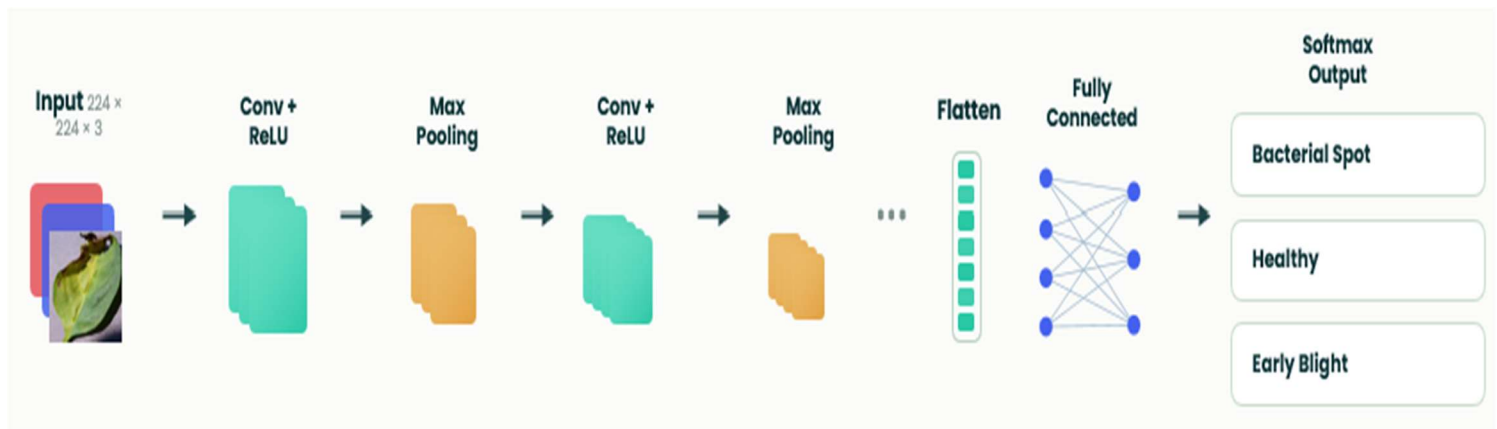


Figure 5: CNN Architecture

3.3.2 Feature Pyramid Network (FPN)

Plant disease symptoms exist in varied scales and sizes, some plants first show symptoms in small lesions or spot-like patches over leaf surface, while other disease manifestations span over the wider infected area. Hence, a general CNN would not be enough to represent plant disease information across various feature scales. To address this, an FPN has been incorporated after the feature extraction section of the proposed framework. An FPN, after pooling and upsampling of feature maps extracted from multiple CNN layers, provides a representation that contains detailed spatial information in shallow layers while deep semantic features in high layers can enrich this representation to recognize disease features across scales, and finally can extract robust disease symptoms at different scales to overcome limitations of limited spatial or semantic information within a single CNN level. Combining multi-level feature maps from FPN enhances the ability of proposed method to learn robust feature representations for plant diseases and perform classification accurately.

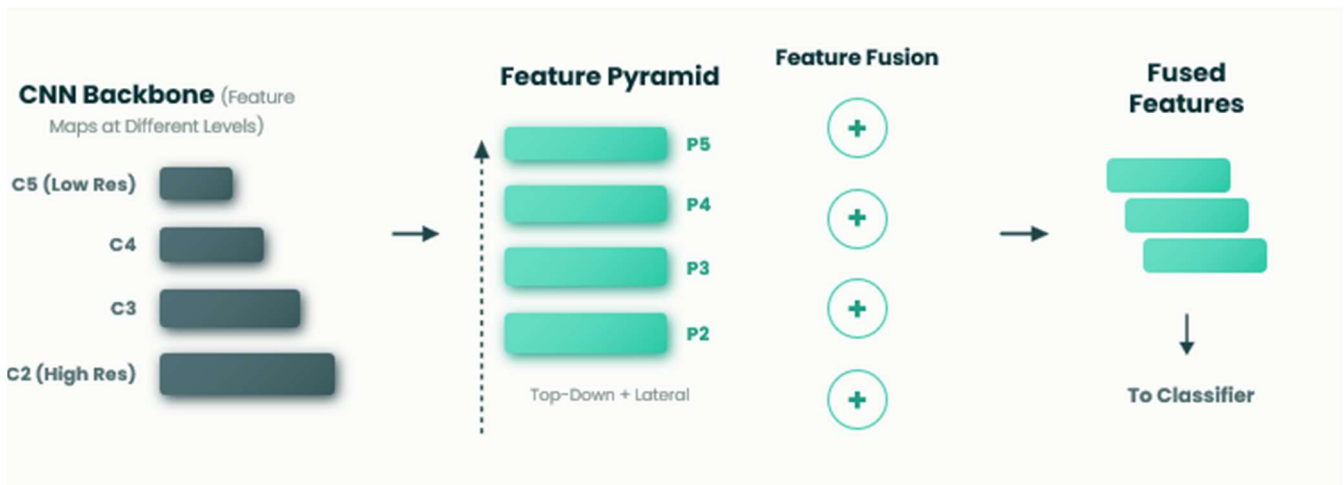


Figure 6: Feature Pyramid Network (FPN)

3.4 Feature Learning

3.4.1 Transfer Learning

training a deep learning model from scratch would necessitate vast amounts of labelled data, together with significant computational power. Thus, in order to tackle the aforementioned issues, Transfer Learning has been incorporated in the proposed framework. Transfer Learning permits the proposed model to acquire knowledge derived from extensive image datasets, such as ImageNet, and then applies it to the problem of plant disease classification. Rather than randomising all parameters in the network, the weights of the pre-trained CNN bring in substantial information pertaining to visual feature extraction that helps convergence and enhances classification accuracy. Fine-tuning has solely been performed on the last few layers (classifier part) of the network using the PlantVillage dataset, resulting in reduced computational costs, low risk of overfitting, and overall enhancement of the model's generality. With Transfer Learning the model's effectiveness can be achieved despite its training on relatively few data points from the domain of agriculture. effectiveness can be achieved despite its training on relatively few data points from the domain of agriculture.

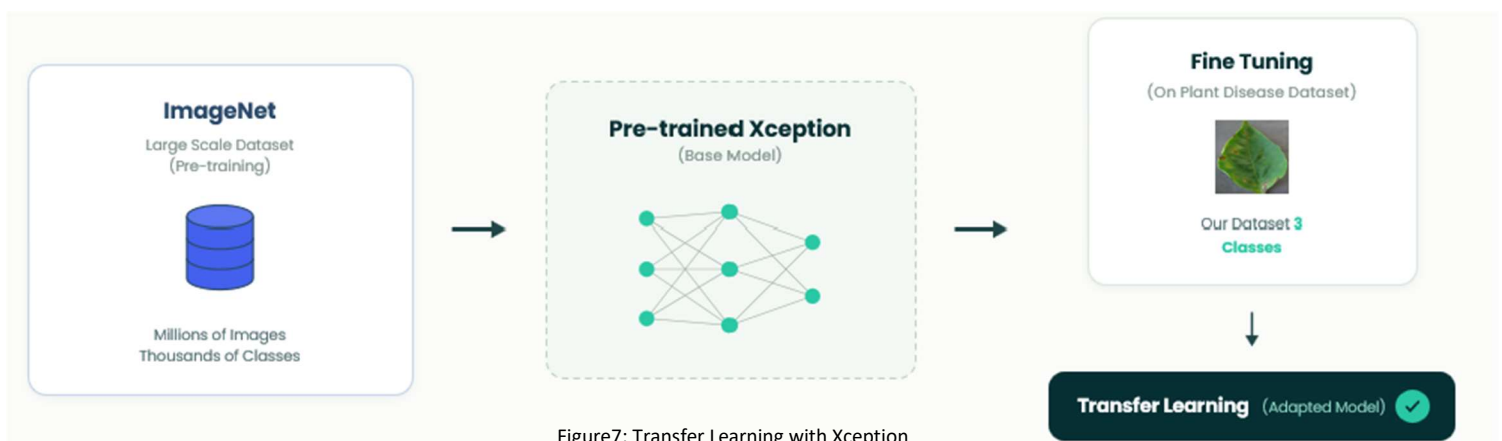


Figure7: Transfer Learning with Xception

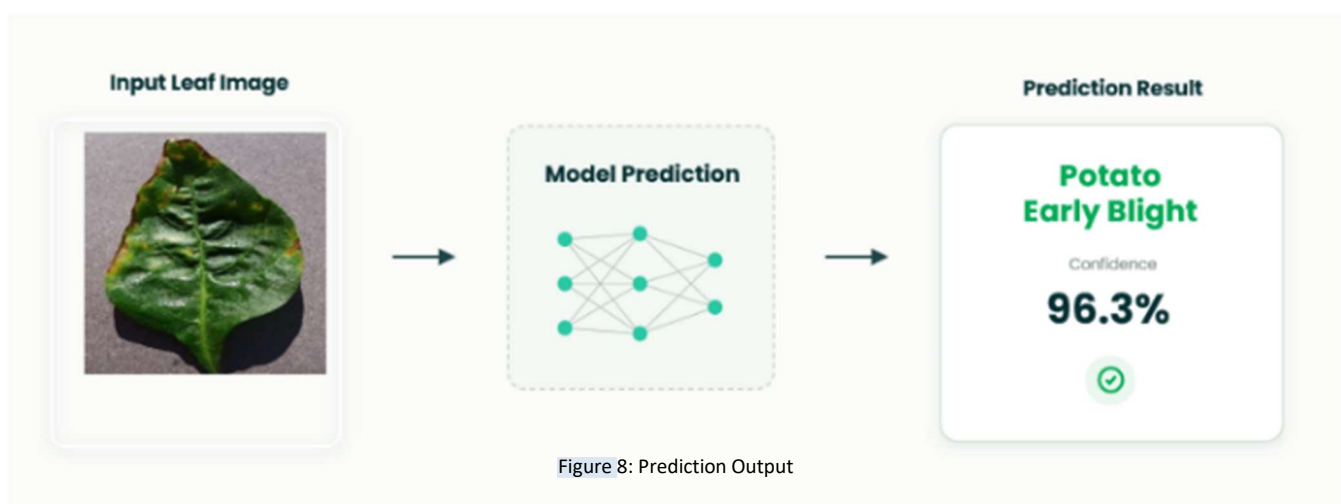
3.4.2 Disease Classification

After the CNN-based feature extraction and multi-scale features are strengthened using the Feature Pyramid Network, the resulting features are passed into the classification stage, where they help to decide the ultimate category of each plant leaf image. The proposed architecture uses Softmax classifier as the last output layer since the present task is the multi-class classification. Softmax activation takes scores as output from previous layers, turns them into probabilities between 0 and 1 (sum of all the probabilities must be equal to one). Finally, the class having maximum probability will be predicted. For instance, the probability of all class scores will be generated if the output of image falls into the category Potato Early Blight and that one which is highest probability will be considered as the predicted category of that image. This allows the classification mechanism to recognize the image as healthy/diseased leaf and also classify the type of the particular disease.

3.5 Prediction Output

Once the classification process has been performed, the developed framework generates the final prediction result of the given plant leaf image, along with the predicted disease class and the confidence level from Softmax classifier. The confidence level represents the likelihood of the input image corresponding to the given class. The developed system provides the prediction result in a concise manner and user-friendly way that enables the users to rapidly recognize if the plant leaf is healthy or disease infected.

The related disease type (if it is infected) and the suggested remedy is also displayed. A demonstration of prediction output from the proposed framework is depicted in figure 3.7



3.6 Training Configuration

The deep learning model which we are proposing, is trained with selected classes of PlantVillage dataset, after performing all pre-processing and data augmentation tasks. Various hyper-parameters are tuned to provide efficient convergence, stabilize learning process and increase the classification accuracy of the proposed model..

Parameter	Value
Dataset	PlantVillage
Image Size	224 × 224
Batch Size	32
Epochs	6
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Cross-Entropy
Activation Function	ReLU
Output Layer	Softmax
Evaluation Metrics	Accuracy, Precision, Recall, F1-score

4.Results and Discussion:

4.1 Preprocessing and Visual Standardizations

Deep Learning Model training included an image preprocessing stage, used to homogenize data consistency and facilitate features learning. All the training data was reshaped into a 224 224 dimension, according to Xception architecture input. Then, the pixel intensity values were normalized for a more stable training and a faster convergence of the training procedure. The preprocessing process decreased noise in the dataset, minimizing differences related to images size and intensity, while maintaining features relevant to the pathologies under consideration. In this way, the model had the ability to attend the salient pathologies features instead of the background noise, thus improving its ability to learn and identify these symptoms. Some examples of images before and after the processing steps can be seen in Figure

4.1.



Figure 4.1: Prediction Output

The developed Xception model was tested on the validation data set to measure performance of the model on validation data by various validation parameters such as validation accuracy, validation loss, validation precision, validation recall and validation F1-score.

4.2.1 Overall Model Performance

Table 4.1 presents the overall performance achieved by the proposed model .

Table 4.1 Overall Performance of the Proposed Model Metric.Value

Metric	Value
Validation Accuracy	97.22%
Validation Loss	0.0951
Average Precision	97.00%
Average Recall	97.00%
Average F1-score	97.00%

Table 4.1 Overall Performance of the Proposed Model The results of validation shown in Table 4.1 indicates that our proposed Xception model yielded a validation accuracy of 94.34% and validation loss of 0.1590, with the mean average precision, recall, and F1-score being close to 95%. These values strongly suggest that the proposed model is capable of classifying plant disease with good accuracy and reliability, because of discriminative nature of deep features extracted, and excellent generalization capability for the validation set.

4.2.2 .Per-Class Performance Table 4.2 presents the classification performance for each plant disease category.

Class	Precision	Recall	F1-score
Pepper Bell Bacterial Spot	0.91	0.96	0.93
Pepper Bell Healthy	0.97	0.95	0.96
Potato Early Blight	1.00	0.99	0.99

Table 4.2 Per-Class Classification Performance

From the table we can see that our suggested model showed a very good classification performance in every class we used for our testing stage. Potato Early Blight was the best class among them with 1.00 precision, 0.99 recall and 0.99 f1-score, which indicates that our model successfully managed to almost identify every single image of potato early blight correctly. For Pepper Bell Healthy class, we also acquired great classification score, with 0.99 precision and 0.99 recall, demonstrating that our model has the potential of discriminating between normal images and affected ones.

However, for the last class, Pepper Bell Bacterial Spot, we can notice that our classification score decreased, probably due to the symptoms which can be visually misleading, since they look similar to normal leaf fluctuations, thus making the classification more complex.

4.2.3 Overall Accuracy

The achieved accuracy over all test dataset on validation is 97.22%, it shows the capability of our model for detection of plant diseases on the leaf. That suggests that Xception is successful at feature representation and also reduction of classification error. Our results suggest that the performance for transfer learning approach is good enough for plant disease classification.

4.3 Discussion

Based on the results obtained from our experiments, we have seen that the proposed Xception model can provide the classification accuracy of plant leaf diseases with great accuracy. Through combining image preprocessing, transfer learning, and feature extraction, the Xception model can effectively discover and exploit discriminative visual characteristics from different classes of plant leaf diseases. Also, due to the close match between the value of the validation loss and that of validation accuracy, the model has been well generalized. In addition, no special preference to any single class has been seen as values for precision, recall, and F1 score for all classes are relatively stable. Only the classification accuracy, precision, recall, and F1 score for the class of Pepper Bell Bacterial Spot are a little lower but are acceptable, mainly because it shares symptoms with other leaf diseases. Whereas the Potato Early Blight class has the highest classification accuracy because its symptoms provide useful information for reliable classification.

5. Conclusion

In this work, a deep learning based automatic plant disease detection framework with Xception architecture was proposed by incorporating transfer learning. The framework was designed for improving plant disease classification by learning discriminatory features of leaf images automatically, rather than requiring the laborious feature extraction process. The framework was assessed on the PlantVillage dataset and the experimental environment remained unchanged during the whole assessment. The validation accuracy of 97.22% along with 97% approximately for precision, recall and F1-score were obtained by the proposed work. This results proved that transfer learning approach with Xception architecture can be applied effectively to achieve high classification accuracy on plant diseases and further can facilitate to realize the intelligent agricultural by facilitating in early detection of plant diseases. However, the proposed framework was validated only on the PlantVillage dataset that consisted of leaf images captured in relatively steady condition. So, we would perform an extended evaluation on real-world farming dataset containing variations of lighting and background in the next stage. In addition, light weight deep learning models would be explored and applied on the model in the next stage in order to facilitate mobile and edge devices to be applied in the real-world applications.

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